Locally Equivalent Weights for Bayesian MrP

Ryan Giordano, Alice Cima, Erin Hartman, Jared Murray, Avi Feller

University of British Columbia Statistics Seminar

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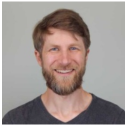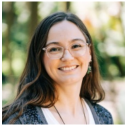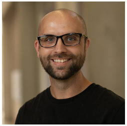

Future work

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But the high level idea can be extended much more widely:

1. Assume your initial model was accurate
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3. Use local sensitivity to detect whether the change is what you expect
4. If the change is not what you expect, either (1) or (2) was wrong

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Checks of this form give generalized versions of many standard linear model diagnostics.

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Regression

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General models

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Consistency / Unbiased	$y = \theta^{\intercal}\mathbf{x} + \varepsilon$ $\tilde{y} = (\theta + \delta)^{\intercal}\mathbf{x} + \varepsilon$ $\hat{\theta}(\tilde{y}) \overset{\text{check}}{=} \hat{\theta}(y) + \delta$	

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Consistency / Unbiased	$y = \theta^\intercal \mathbf{x} + \varepsilon$	$y = f(\mathbf{x}, \varepsilon, \theta)$
	$\tilde{y} = (\theta + \delta)^\intercal \mathbf{x} + \varepsilon$	$\tilde{y} = f(\mathbf{x}, \varepsilon, \theta + \delta)$
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Exogonous residuals	$y = \theta^\intercal \mathbf{x} + \varepsilon$ $\tilde{y} = y + \varepsilon z$ $\hat{\theta}(\tilde{y}) \overset{\text{check}}{=} \hat{\theta}(y)$	$y \sim \mathcal{P}(y\vert\mathbf{x})$ and $\mathcal{P}(\mathbf{x}) = w$ $\tilde{w} = w + \delta z$ $\hat{\theta}(\tilde{w}) \overset{\text{check}}{=} \hat{\theta}(w)$

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Fisher information	$\mathcal{I} :=$ Fisher information $\Sigma :=$ Score covariance $\mathcal{I}^{-1} \overset{\text{check}}{=} \Sigma$	$y \sim \mathcal{P}(y\|\theta)$ $\tilde{y} \sim$ Importance sample y using $\tilde{w} = \frac{\mathcal{P}(y\|\hat{\theta} + \delta)}{\mathcal{P}(y\|\hat{\theta})}$ $\hat{\theta}(\tilde{w}) \overset{\text{check}}{=} \hat{\theta}(1) + \delta$

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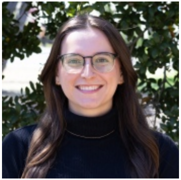
Future work

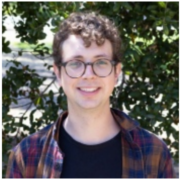
Student contributions and ongoing work:

- **Vladimir Palmin** is working on extending MrPlew to `lme4`
- **Sequoia Andrade** is working on generalizing to other local sensitivity checks
- **Lucas Schwengber** is working on novel flow–based techniques for local sensitivity
- **(Currently recruiting!)** Doubly–robust Bayesian Hierarchical MrP

Vladimir Palmin



Sequoia Andrade



Lucas Schwengber

Preprint and R package (hopefully) coming soon!

References i